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ADAPTIVE DECISION MAKING SUPPORT SYSTEM, BASED ON FUZZY LOGIC CONCLUSION

The paper contains the description of adaptive decision making support system, based on fuzzy logic rules, the system takes into account the results of objects behavior forecast and can be applied in conditions of fuzziness.

Key words: *decision making support system, fuzzy logic, adaptive system, forecast of random process.*

Actuality

Decision making is one of the most important stages for any purposeful human activity. In engineering branches they are always considered and taken into account before the development of technology aimed at creation of new devices, selection of control actions needed for control of complex installations and systems, etc. That is why, nowadays there exists the necessity to create system of decision making support, that would involve the consecutive application of the methods of qualitative and quantitative character needed for analysis of development of the phenomenon being studied.

There exist various approaches to the development of decision making support systems, using different tools: correlative and regressive analysis, scenario methods, game theory, fuzzy logic, etc. But practically all the previous expert systems simulated the process of decision making by the expect as deductive process using the conclusion, based on classification rules. It meant, that the totality of rules “if … then” was embedded in the system, according to which a solution of the needed problem was generated on the base of input data.

In recent years “nonclasic” approach in the theory of decision making and control has been developed. This approach assumes the application of the algorithms, based on fuzzy logic, neural networks and genetic algorithms, scenario methods, etc. Besides, situation control, based on hierarchical models with fuzzy parameters models and decision making algorithms for protection of information, based on methods of artificial intelligence are widely used [1].

The application of the results of modeling and forecast of random processes, describing behavior is an important step in the process if decision making to improve their efficiency and decrease probability of making decisions. That is why, not only the study how the forecast results influence the evaluation of alternative decisions, but the elaboration of adaptive system of decision making support, based on the results of random processes forecast is very actual.

As it is known, decision making in problem –oriented information systems and control systems is carried out in conditions of a priori uncertainty, stipulated by inaccuracy or incompleteness of initial data. Stochastic nature of external impacts, lack of adequate mathematical model, non-precise formulation of the aim, human factor [1, 2] etc. Uncertainty of the system can lead to increase of risks of non-efficient decision making as a result negative economic, technical and social consequences can be observed.

Uncertainty in decision making system is compensated by different methods of artificial intelligence. For efficient decision making in condition of uncertainty of system operation, methods based on fuzzy logic rules are applied.

Such methods are based on fuzzy sets and use linguistic values and expressions for the description of decision making strategy [3]. One of the methods, the authors suggest to apply for the development of decision making support system, is the method of fuzzy logic conclusion. This is a convenient mechanism of decision making problems solution, providing the transparence of decision making algorithm, easiness of its correction, it provides the possibility to take into consideration quantitative changes and qualitative characteristics of modeled systems.

Problems set-up

The aim of the given research is to develop adaptive approach, based on fuzzy logic rules, the creation of expert systems of decision making support, which can take into account the results of objects behavior forecast and be efficiently used in uncertainty conditions.

Elaboration of block diagram of adaptive control system of decision making support based of fuzzy logic conclusion

Adaptation is the process of system parameters, structure and action change, based on current information in order to achieve optimum state of the system in conditions of uncertainty in changing operation modes.

Adaptive system (self-learning system) – is a system, operation algorithm of which is constructed and improved in the course of self-learning. This process is reduced to “tries” and “errors”. The system performs test changes of the algorithm and simultaneously controls the results of these changes. If they are favorable, form the point of vue of the aims of control, then changes develop in the same direction to obtaining the best results or to the start of worsening of control process [4, 5].

Block diagram of adaptive system decision making support, based on fuzzy logic conclusions, is shown in Fig. 1.

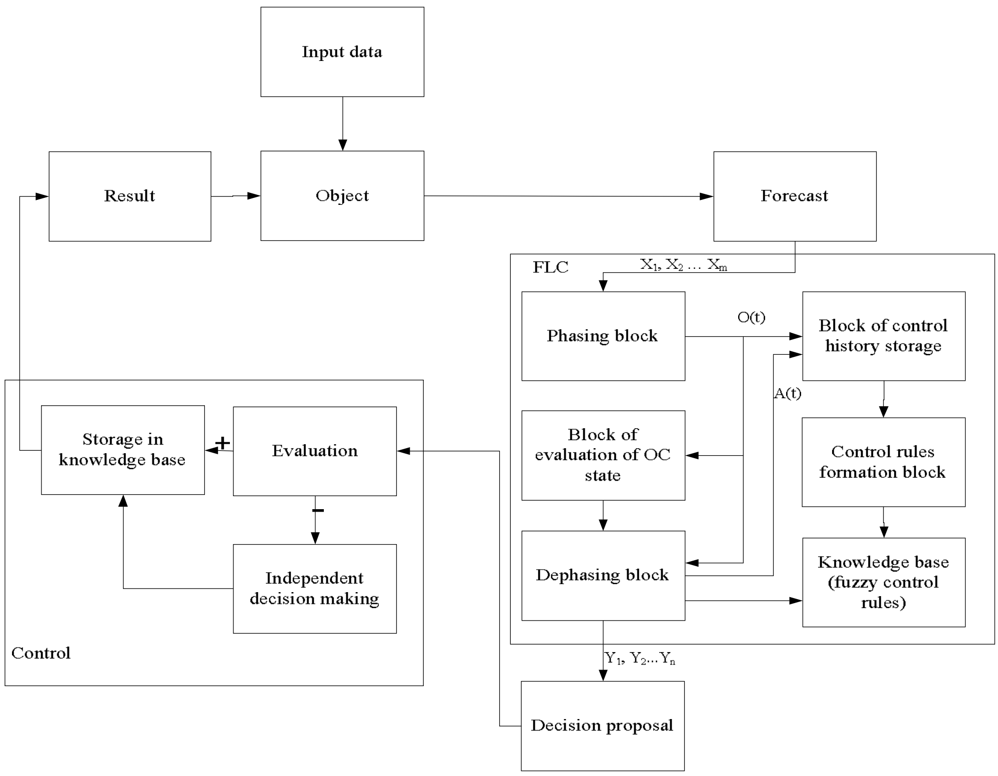

Fig. 1. Block diagram of adaptive control system of decision making support, based on fuzzy logic conclusion

The given system is constructed, taking into account the results of the forecast of control object (CO) future behavior and procedures of knowledge obtaining from experts in the sphere of decision making.

On the basis of the suggested block diagram the process of decision making by means of adaptive system comprises the following stages:

Stage 1. Formation of knowledge base/adding new information, realized in two subsrages. The first substage is carried out while filling the base with expert data. The second substage is filling of knowledge base with new case, being considered in the process of system operation. After decision making and evaluation of the results current situation becomes previous case and is stored in the data base. Negative result is also informative and is stored in the base.

Stage 2. Forecast is the description of object being studied, behavior by means of mathematical model. We are to determine the type of random process, corresponding to the object, applying the set of identification tests and then choose corresponding mathematic model and test it for adequacy and forecast ability. If the results are satisfactory, the given model will be used a s a tool for evaluation factors, the user takes into account while decision making.

Stage 3. Formation of fuzzy logic conclusion (FLC), comprising several blocks. We will consider their formation in details (see Fig. 1).

Phasing block. In this block, the process of phasing occurs – construction of fuzzy sets for linguistic terms of input parameters – factors of object sate evaluation: x_1, x_2... x_m.

Block of evaluation of OC state forms logical conclusion, based on phasing values *O(t)*, which are transmitted to dephasing block. Dephasing is realized by means of fuzzy set transformation into defined number, Dephasing procedure is a procedure of obtaining decision by means of fuzzy model. The results of dephasing *A(t)* are stored in knowledge base and in the block of control history storage. New rules of control can be formulated on the base of control history data *A(t)* and *O(t).* For the given stage value *Y* at the output is the result of decision making by means of fuzzy logic conclusion, transmitted at the next control – block.

Stage 4. Control is performed by the user to evaluate the decision, generated and perform the action. If the user agrees with the given decision, he confirms it. If he does not agree, he must perform the procedure of decision making himself. Data, regarding the case and results are stored in knowledge base [6].

Hence, while user's operation with the system its adaptation to user's peculiarities occurs due to information, obtained as a result of decisions taken or not taken by the user.

Elaboration of mathematical model for the forecast of random process

The characteristic feature of adaptive systems is self-learning or ability to adjust internal parameters to the dynamics of forecasted random process. Training can be performed both "without a teacher" and "with a teacher": in the first case model parameters variation occurs in accordance with internal algorithm, embedded in the model, and in the second case the instruction, what change is better or worse is needed. For greater part of situations the value of forecast error, called efficiency function is used as "teacher's opinion", the aim of training is to adjust parameters so that this value be minimum. Prior to the stage of decision making, it is necessary to consider the analysis and forecast of random processes, describing the behavior of the object of control.

Analysis of random processes comprises the following stages:

- identification of random process type;
- modeling of the process;
- forecasting of its behavior.

The type of random process requires the construction and application of corresponding mathematical models for their analysis and forecast. Two basic classes of random process are distinguished – stationary and non-stationary. But in recent decades different nature of tome series has been observed, different form classic. These are so called processes with long memory, which occupy intermediate place in classification between stationary (short memory) and non-stationary (infinite memory) and require the development of new models for their mathematical description.

Taking into account various nature of random processes, prior to the their analysis, it is necessary to determine the type of the process.

For verification of stationary and determination of integration order of investigated series several alternative tests are used. All the tests can be divided into large categories, depending on what hypothesis is considered to be zero. Expanded test Dikki-Fuller (ADF) and Phylips – Perrom Test

(PP), that are one of the most popular and known tools for analysis of time series behaviour, verify zero hypothesis regarding non-stationary of the process at alternative hypotheses that the process is stationary [2, 3]. Besides there exists one more powerful test for verification of series stationary – KPSS test, elaborated by Kviatkovskiy, Phillips, Schmidt, Shin. Unlike Dikki – Philips test, it verifies zero hypothesis regarding initial series stationary. For long memory testing, there exist one more test, belonging to this group – LoMac test.

After performing ADF, KPSS and LoMac tests the identification of random process can be performed and its type can be determined – stationary, non-stationary, with long memory [3].

Further it is to select mathematical model in accordance with the type of random process. For their description the following mathematical models were selected:

– for stationary random process:

$$\begin{aligned} &\varphi(L)y_t = \Theta(L)\varepsilon_t \\ &\varepsilon_t \approx i.i.d.D(0,1), \end{aligned} \tag{1}$$

– for non-stationary random process:

$$\begin{aligned} &\varphi(L)y_t = \Phi(L)(1-L)^d y_t = \Theta(L)\varepsilon_t \\ &\varepsilon_t \approx i.i.d.D(0,1), \end{aligned} \tag{2}$$

– for the process with long memory:

$$\begin{aligned} &\varphi(L)(1-L)^d y_t = \Theta(L)\varepsilon_t \\ &\varepsilon_t \approx i.i.d.D(0,1) \end{aligned}, \tag{3}$$

where

$$(1-L)^d = 1 - dL - \frac{\alpha(1-d)}{2!}L^2 - \frac{\alpha(1-d)(2-d)}{3!}L^3 - \ldots = \sum_{k=0}^{\infty}\frac{\Gamma(k-d)}{\Gamma(-d)\Gamma(k+1)}L^k = 1 - \sum_{k=0}^{\infty}c_k(d)L^k$$

$0 < d < 1$, $c_1(d) = d$, $c_2(d) = \frac{1}{2}d(1-d)$,... and $\Gamma(.)$ means gamma-function $\Gamma(z) = \int_0^{\infty} t^{z-1}e^{-t}dt$;

$\Phi(L) = 1 - \psi_1 L - \ldots - \psi_p L_p; \Theta(L) = 1 + \theta_1 L + \ldots + \theta_q L_q$ – are log operators of autoregressive process and sliding average, correspondingly; ε_t – «white noise».

We can mention one more characteristic of random process, influencing the adequacy of mathematical model, - it is phenomenon of heteroskedasticity. If remainders of time series have constant dispersion, then these series are called homoskedastic, if they are not constant – they are heteroskedastic. For determination we suggest to use Lunge-Box test and White test.

After identification of heteroskedastic type of the process, it is necessary to choose mathematical model, describing its behavior. In the give paper we consider the stages of mathematical models development fir various types of heteroskedastic processes.

Stationary processes. Let us consider random process y_t. Let us assume that after identification of process type and selection of adequate model , describing time series, the conclusions was drawn, that process y_t. is stationary and is described by the model ARMA (*p, q*) with parameters *p* and *q*. We will apply GARCH-methods for correction of the obtained model [4].

This process can be presented as ARMA (*m*, *p*) process:

$$[1-\alpha(L)-\beta(L)]\varepsilon_t^2 = \alpha_0 + [1-\beta(L)]v_t, \tag{4}$$

where $m = \max\{p,q\}$ and $v_t \equiv \varepsilon_t^2 - h_t$.

Formally, ARMA-GARCH (*p*, *q*) model can be determined in the following way:

$$\begin{aligned}
&\Phi(L)y_t = \Theta(L)\varepsilon_t \\
&\varepsilon_t = h_t z_t \\
&z_t \approx i.i.d.D(0,1) \\
&h_t = \alpha_0 + \alpha(L)\varepsilon_t + \beta(L)h_{t-1}\ ,
\end{aligned} \qquad (5)$$

where $D(.)$ – is distribution density function .

Non-stationary process. Let after identification of the process type and selection of adequate model describing time series, the conclusions was drawn, that process y_t be non-stationary and is described by ARIMA (p, d, q) model with p, d and q parameters. Let us apply GARCH-methods for correction of the obtained model. Then, formally model ARIMA- GRACH (p, d, q) can be determined in the following way:

$$\begin{aligned}
&\Phi(L)\omega_t = \Theta(L)\varepsilon_t \\
&\omega_t = \Delta^d y_t \\
&\varepsilon_t = h_t z_t \\
&z_t \approx i.i.d.D(0,1) \\
&h_t = \alpha_0 + \alpha(L)\varepsilon_t + \beta(L)h_{t-1}\ .
\end{aligned} \qquad (6)$$

Processes with long memory. Since in the given paper we assume to apply fractionally integrated AFRIMA models for modeling series with long memory, characterized by hyperbolic autocorrelation function, special classes of GARCH-models were developed for such case FIGARCH and HYGARCH [5, 6].

Partially integrated process GARCH (or FIGARCH (p, d, q)) can be described by replacing in model GARCH operator of first differences (1-L) by operator of partial differentiation (1-L)d, where d – is memory parameter and $0<d<1$:

$$\Phi(L)(1-L)^d\varepsilon_t^2 = \alpha_0 + [1-\beta(L)]v_t\ . \qquad (7)$$

The possibility to apply d values in the interval from zero to unity will give the model additional flexibility, that can be useful while modeling of long-term dependences, characteristic for conventional dispersion of numerous time series, for instance, financial [6].

Formally, model ARFIMA-FIGARCH (p, d, q) can be determined in the following way:

$$\begin{aligned}
&\Phi(L)(1-L)^d(y_t-\mu) = \Theta(L)\varepsilon_t \\
&\varepsilon_t = h_t z_t \\
&z_t \approx i.i.d.D(0,1) \\
&h_t(\alpha_o,\varphi,\beta,d) = \alpha_0 + [1-(1-\beta(L))^{-1}\varphi(L)(1-L)^d\varepsilon_{t-1}^2\ .
\end{aligned} \qquad (8)$$

The model simultaneously assumes availability of long memory, using various types of errors distribution and inclusions of some additional variables [7].

In practice, as a rule, models, ARFIMA-FIGARCH (1, d, 0) or ARFIMA-FIGARCH (1, d, 1), are used , parameter d is calculated, applying the method of maximum likelihood.

It was established, that FIGARCH – processes are also non-stationary, as classic GARCH. It means, that the concept of single root existence, characteristic for linear processes is difficult to apply for non-linear processes. Besides, it is difficult to choose memory parameter d, that model FIGARCH were adequate and had high power forecast. To avoid the above- mentioned difficulties, class of FIGARCH- models was expanded. In the given paper model HYGARCH(p, d, q) is suggested, this model, unlike the existing ones, describes hyperbolic process GARCH.

У HYGARCH models operator $(1-L)^d$ is replaced by $[(1-\alpha)+\alpha(1-L)]^d$. Then, model

HYGARCH can be determined as:

$$h_t = \alpha_0 (1-\beta(L))^{-1} + [1-(\varphi(L)(1+\alpha[(1-L)^d - 1]))(1-\beta(L))^{-1}\varepsilon_t^2, \quad (9)$$

where parameters α and d are assumed to be positive (α >0, d >0).

Formally, model ARFIMA– HYGARCH (p, d, q) can be determined in following way:

$$\begin{aligned}
&\Phi(L)(1-L)^d (y_t - \mu) = \Theta(L)\varepsilon_t \\
&\varepsilon_t = \sigma_t z_t \\
&z_t \approx i.i.d.D(0,1) \\
&h_t = \alpha_0 (1-\beta(L))^{-1} + [1-(\varphi(L)(1+\alpha[(1-L)^d - 1]))(1-\beta(L))^{-1}\varepsilon_{t-1}^2 .
\end{aligned} \quad (10)$$

Hence, prior to passing to the stage of formation of fuzzy logic conclusion and decision making on its base, it is necessary to evaluate object behavior, i.e., identify time series, which describes it, and choose corresponding mathematical model for its description from the models, considered in the given subsection.

Application of Mamdani algorithm for fuzzy logic conclusion formation

Evaluation of decision in the given adaptive system is realized by means of methods, based on fuzzy logic rules, namely – fuzzy logic conclusion.

There exists several algorithm of fuzzy conclusion: Mamdani, Sugeno and Larsen. The most popular among them is Mamdani algorithm. Transparence of Mamdani fuzzy models is one of the main advantages, due to which fuzzy technologies successfully compete with other methods. They are most suitable for those applied parameters, where the possibility of content interpretation is more important that the accuracy of modeling.

We will illustrate the application of the given method on the example of decision making rules elaboration for financial markets.

Let the base of fuzzy rules of decision making contain dependences of profit, determined by experts from certain input variable X_1 and X_2, where X_1 – is price position of financial assets relatively sliding average (SA), and X_2 – is interest rate variation . We will introduce linguistic variables: X_1 = *(H, MH, L, ML)*; X_2 = (decrease of rate, constant rate, increase of rate); Result = (greater profit, low profit, low losses, great losses).

Below we will consider some of the possible rules:

R_1: if $X_1 \in L$ i $X_2 \in$ constant rate, then the results is low losses;

R_2 : if $X_1 \in H$ i $X_2 \in$ rate decrease, then the results is low losses;

R_3 : if $X_1 \in L$ i $X_2 \in$ rate decrease, then the result is great profit.

Suppose, that linguistic terms of inputs are described by such fuzzy sets:

H = {-2/0; -1,5/0; 0/0,2; 1,5/0,6; 2/0,3};

L = {-2/0,1; -1,5/0,5; 0/0,2; 1,5/0; 2/0};

constant rate = {-0,25/0,2; -0,2/0,5; 0/1; 0,2/0,4; 0,25/0,15};

decrease of rate = {-0,25/0,5; -0,2/0,2; 0/0; 0,2/0; 0,25/0}.

Output terms are described by such sets:

low losses = {-150/0,5; -100/1; 0/0,1; 100/0; 150/0};

large profit = {-150/0; -100/0; 0/0; 100/0,1; 150/0,6}.

It is necessary to determine the result at *ML* and rate increase.

Pay attention that input data do not determine *ML* terms and rate increase. Initial reaction on these fuzzy value it is necessary to obtain in the process of logic conclusion, on the basis of rules base.

Let fuzzy sets arrive at system input:

ML = {-2/0,7; -1,5/0,25; 0/0; 1,5/0; 2/0};

and rate variation :

rate increase = {-0,25/0; -0,2/0; 0/0; 0,2/0,2; 0,25/0,5}.

Operations of minimum and maximum determination we will denote by $\wedge$ and $\vee$ correspondingly.

For computation of the output we will carry out stages of fuzzy logic conclusion :

1. Обчислення рівнів істинності правил.

a_1 = min[max(0,7^0,1; 0,25^0,5; 0^0,2; 0^0; 0^0), max(0 ^0,2; 0^0,5; 0^1; 0,2^0,4; 0,5^0,15)] = min[max(0,1; 0,25; 0; 0; 0), max(0; 0; 0; 0,2; 0,15)] = min[0,25; 0,2] = 0,2

a_2 = min[max(0,7^0; 0,25^0; 0^0,2; 0^0,6; 0^0,3), max(0 ^0,5; 0^0,2; 0^0; 0,2^0; 0,5^0)] = min[max(0; 0; 0; 0; 0; 0), max(0; 0; 0; 0,2; 0,15)] = min[0; 0] = 0

a_3 = min[max(0,7^0,1; 0,25^0,5; 0^0,2; 0^0; 0^0), max(0 ^0,5; 0^0,2; 0^0; 0,2^0; 0,5^0)] = min[max(0,1; 0,25; 0; 0; 0), max(0; 0; 0; 0; 0)] = min[0,25; 0] = 0.

2. Computation of rules.

B_1 = {-150/min(0,2; 0,5); -100/ min(0,2; 1); 0/ min(0,2; 0,1); 100/ min(0,2; 0); 150/ min(0,2; 0)} = {-150/0,2; -100/0,2; 0/0,1; 100/0; 150/0};

B_2 = {-150/min(0; 0,5); -100/ min(0; 1); 0/ min(0; 0,1); 100/ min(0; 0); 150/ min(0; 0)} = {-150/0; -100/0; 0/0; 100/0; 150/0};

B_3 = {-150/min(0; 0,5); -100/ min(0; 1); 0/ min(0; 0,1); 100/ min(0; 0); 150/ min(0; 0)} = {-150/0; -100/0; 0/0; 100/0; 150/0};

3. Outputs aggregation.

$B=B_1 \vee B_2 \vee B_3$ = {-150/max(0,2; 0; 0), -100/max(0,2; 0; 0), 0/max(0,1; 0; 0), 100/max(0; 0; 0), 150/max(0; 0; 0))} = {-150/0,2; -100/ 0,2; 0/0,1; 100/0; 150/0}.

4Output dephasing.

$$y = \frac{-150 \cdot 0{,}2 - 100 \cdot 0{,}2 + 0 \cdot 0{,}1 + 100 \cdot 0 + 150 \cdot 0}{0{,}2 + 0{,}2 + 0{,}1 + 0 + 0} = -100.$$

Thus for the given fuzzy sets at *ML* and rate increase, the result will be low losses.

Taking into account the above-mentioned, we will determine the stage of decision making in conditions of uncertainty, using Mamdani:

1) choice of X_k, factors, on their base the decision will taken. For each factor, the set of its values is specified (term-set), membership functions for each linguistic term form basic term-set are specified. Truth level for each a_m rule is determined;

2) computation of the outputs of each B_m rules using minimum operation;

3) unite of all fuzzy sets, obtained at the output of rules, using maximum operation into a single fuzzy set B;

4) transition from fuzzy set to exact value y (if it necessary).

Hence, usage of fuzzy logic conclusion block for decision making, has the following advantages: possibility to operate fuzzy input data, fuzzy formalization of evaluation and comparison criteria, introduction of dependences in a language, close to natural.

Adaptive system of decision making support «TradeKeeper»

On the basis of the above-described approach to decision making in conditions of uncertainty, expert adaptive system «TradeKeeper» was developed. The given system enables the user to analyze behavior of the assets and, as a result, facilitates decision making and improves its efficiency. «TradeKeeper» consists of the following components: common and user's interface. The system provides the possibility to register and work under individual login. Each user uses his own knowledge base and mechanism of fuzzy logic output for creation of decision making, strategy [14].

Process of initial sample formation is realized on the basis of decisions, obtained from the authors on financial market, solving real problems. In the process of system application, the sample changes with each decision taken, forming user's own knowledge base, takes into account the characteristic features of his work and psycho-emotional peculiarities.

The following factors are used for decision making:

X_1 – is price position relatively sliding average (linguistic type of the factor);

X_2 – is interest rate change (quantitative type of factor);

X_3 – is observance of price model, change of interest rate (linguistic type of factor);

X_4 – is subjective state of trader (discrete type of factor).

Possible results of decision making are the following:

Class 1 – low profit (less than 1%);

Class 2 – great profit (more than 1%);

Class 3 – low losses (less than 1%);

Class 4 – great losses (more than 1%).

The system provides the possibility by means of on-line resources Yahoo. Finance to obtain quotations of necessary financial tools

Performing certain operations, the user can create his own strategy. The obtained strategy helps to take decisions regarding further successful trade. Fig. 2 shows the example of the strategy, built with the help of strategies master.

Besides, the system allows not only create management strategies and analysis of financial operations, also the user can create his own indicators, establish and change their parameters, conditions, add new rules of classification and fuzzy control rules in knowledge base, that uses them.

Conclusions

Adaptive system of decision making support, based on fuzzy logic conclusion is developed; the given system takes into account the results of the forecast of random processes behavior (stationary, non-stationary, with long memory), describing object of management. Such system can be efficiently applied for decision making, for instance, at securities markets while working with financial assets or in other branches a human activity.

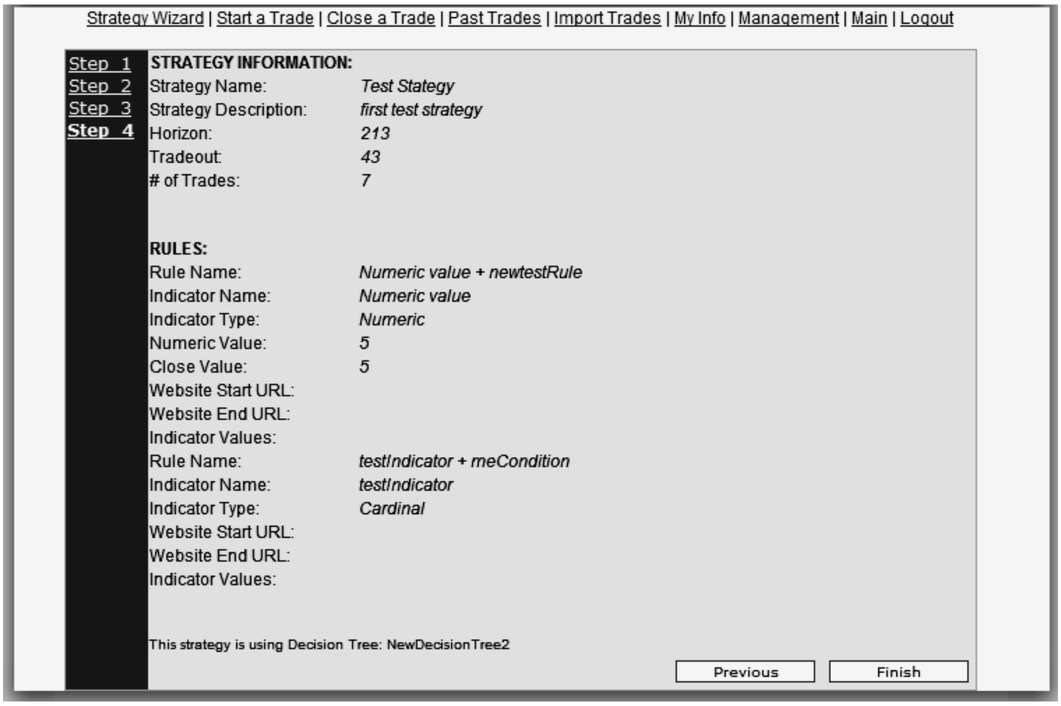

Fig. 2 Example of strategy, built with the help of strategies master

Block diagram of such adaptive system is built; stages of its work with the user are described, the example of Mandany algorithm application for fuzzy logic conclusions formation is given. Adaptive decision making support system enables to accumulate knowledge regarding decisions, taken by the user, in data base and use it for fuzzy logic conclusion.

The developed model of adaptive system is realized in the form of decision support system "Tradekeeper" for operation with financial assets. The given system uses fuzzy mechanism of automatic classification of decision, taken by the user, depending on the expected value of profit as the signal for opening of certain position. The given function is the advantage of "Trade keeper" system, since it increase the efficiency of decisions, taken by the user and allows to obtain maximum profit as a result of financial operation, carried out.

REFERENCES

1. Бочарников В. П. Fuzzy-технология: Математические основы. Практика моделирования в экономике / В. П. Бочарников. – Санкт-Петербург: «Наука» РАН, 2001. – 328 с.
2. Субботін С. О. Подання й обробка знань у системах штучного інтелекту ті підтримки прийняття рішень: Навчальний посібник/ С. О. Субботін. – Запоріжжя: ЗНТУ, 2008. – 341 с.
3. Блюмин С. Л. Модели и методы принятия решений в условиях неопределенности / С. Л. Блюмин, И. А. Шуйкова. – Липецк: ЛЭГИ, 2001. – 138 с.
4. Попов Е. П. Теория систем автоматического регулирования / Е. П Попов., В. А. Бесекерский. – М.: Наука, 2003. – 759 с.
5. Ропштейн А. П. Нечеткая надежность алгоритмических процессов / А. П. Ропштейн, С. Д. Штовба. – Винница: Континент – ПРИМ, 1997. – 142 с.
6. Kvetniy R. N. Using of adaptive approach to make decision in difficult systems / R. N. Kvetniy, V. Y. Kotsubinskiy, L. N. Kislitsa, N. V. Kazimirova // Матеріали Міжнародної науково-технічної конференції «ІРТК-2009», 2009. – С. 15 – 17.
7. Ферстер Э. Методы корреляционного и регрессионного анализа / Э. Ферстер, Б. Ренц. – М.: Финансы и статистика, 1983. – 302 с.
8. Бокс Дж. Анализ временных рядов. Прогноз и управление. Вып. 1 / Дж. Бокс, Г. Дженкинс. – М.: Мир, 1974. – 408 с.
9. Кендалл М. Многомерный статистический анализ и временные ряды / М. Кендалл, А. Стьюарт. – М.: Наука, 1976. – 265 с.
10. Bollerslev T. Fractionally integrated generalized autoregressive conditional heteroskedasticity / T. Bollerslev, R. T. Baillie, H. O. Mikkelsen // Journal of econometrics. – 1996. – № 74, – P. 3 – 30.
11. Baillie R. T. Analyzing inflation by the fractionally integrated ARFIMA-GARCH model / R. T. Baillie, C.-F. Chung, M.A. Tieslau // Journal of Applied Econometrics. – 1996. – № 15.– P. 12 – 60.
12. Штовба С. Д. Введение в теорию нечетких множеств и нечеткую логику [Електронний ресурс] // Режим доступу: http://matlab.exponenta.ru/fuzzylogic/book1/index.php.
13. Кравець П. Системи прийняття рішень з нечіткою логікою / П. Кравець, Р. Киркало // "Вісник національного університету "Львівська політехніка". – 2009. – № 650. – С. 115 – 123.
14. Р. Н. Квєтний Адаптивна експертна система підтримки прийняття рішення в Internet-трейдингу / Р. Н. Квєтний, В. Ю. Коцюбинський, Л. М. Кислиця, Н. В. Казимірова // Міжнародний науково-технічний журнал «Інформаційні технології та комп'ютерана інженерія». – Вінниця.: ВНТУ, 2009. – Вип.№ 2(15). – С. 81 – 85.

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